PRODUCTION SCHEDULING AND CONTROL TECHNOLOGIES: A SYSTEMATIC LITERATURE REVIEW

Pedro Pfeifer Portela Santos (UFSC)
pedro.portela@grad.ufsc.br
Enzo Morosini Frazzon (UFSC)
enzo.frazzon@gmail.com
Ricardo Pimentel (UFSC)
pimentel.egm@gmail.com

Recent works have been directed towards the development of new scheduling and control of production processes technologies. The increasing complexity in production demands more dynamicity in decision making. In this context, this work aims to systematically classify published literature and report the state of the art in cyber-physical systems and industry 4.0. Regarding scheduling and control, this work encompasses concepts and studies the convergence of different research themes, contextualizing its potential. Main trends will be outlined and application areas will be investigated. On this direction, the work identifies the current gaps and discusses future prospects.

Palavras-chave: Cyber physical systems, industry 4.0, adaptive scheduling, simulation-based optimisation

1. Introduction

The increasing complexity in production calls for the parallel development of scheduling and control technologies. In order to handle a higher number of product variants and decreased lot sizes, decision making needs to become more dynamic. Therefore, production planning and control requires reliable, efficient and flexible scheduling methods. Some approaches to solving scheduling tasks are optimisation techniques, such as mixed-integer programming (MULA et al., 2010). Even though the algorithmic power of solvers for this type of problem formulation improved during the last decades, most real manufacturing systems are too complex to be modelled and solved without ample simplifications.

In addition, manufacturing systems feature a wide range of dynamics influences. In literature, it is suggested that complex dynamic problems can be solved appropriately by simulation-based optimization (SBO) (GE et al., 2014; LIN; CHEN, 2015). The combination of both allows for a dynamic scheduling and control of more complex manufacturing systems.

The increasing use of sensor-equipped collaborating machines, often referred to as Industry 4.0 (KAGERMANN et al., 2013), and the continuous development of cyber-physical system technologies enables the real-time collection of a great quantity of data regarding the current state of the system. This pulls the optimization from the basic scheduling level closer to the real processes and holds the potential to provide real-time reactions on the production system. This work aims to report the state of the art in cyber physical systems and the technologies being developed under the context of Industry 4.0 with the intent of systematically classifying the published literature and outlining the convergence of the research themes and possible applications of new technologies. Disturbances that occur in real manufacturing systems are a challenge to existing scheduling and control methods and, thus, this paradigm has the potential of assisting and enabling approaches that can provide flexible and immediate reactions to dynamic changes.

The remainder of the work is organized as follows. In Section 2, an overview of the bibliometric method is provided. In Section 3, we comment about the most relevant information taken out of the data, organized in terms of publication years, authors and articles. Sections 4, 5 and 6 details the literature review of the hybrid approach of simulation and optimization in manufacturing systems, optimized scheduling in dynamic manufacturing systems and cyber-physical production systems. Ultimately, conclusions and directions for future works are presented in Section 7.

2. Review Methodology

This research aims to identify and summarise available literature on the current status of cyber-physical systems and Industry 4.0. In doing so, the convergence of research themes and enabling technologies for production scheduling and control are highlighted. The research method of this review is similar to that of Uriona et al. (2012). However, the search in conference papers was limited to the last ten years, so that recent works on methods yet to be published in peer-reviewed journal papers are also identified and works that may not be relevant anymore are excluded. Bibliometric analyses uses bibliographical data stored on electronic databases in order to provide quantitative data to support a literature review. Inferences are made under the premise that different databases contain different data, therefore, choosing an adequate database to carry out the study is a key step.

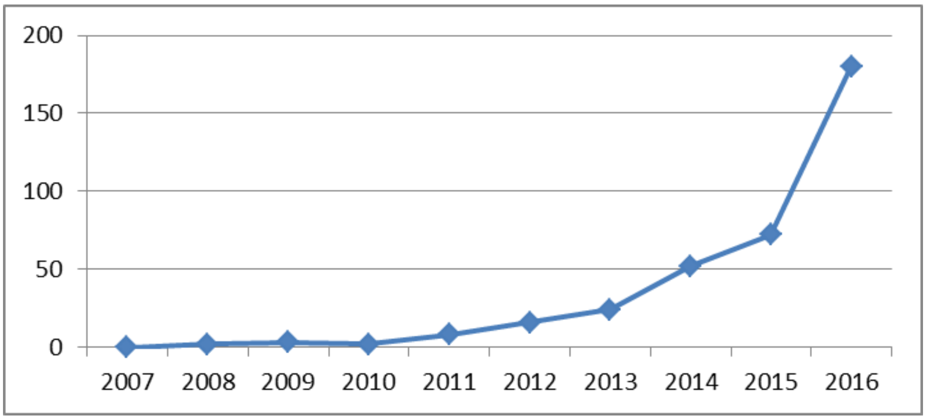
The Web of Science, owned by Thomson Reuters, is considered to be the most important source of data for bibliometric analysis in sciences. Moreover, the Web of Science is comprised of three sub-field databases: the Science Citation Index Expanded (SCI), the Social Sciences Citation Index (SSCI) and the Arts and Humanities Citation Index (AHCI) and accounts for approximately 10,000 journals of a total of around a million that circulates worldwide, reason by which it was dubbed as the database that contains the ‘‘mainstream’’ journals of all sciences (OKUBO, 1997). In order to retrieve a relevant sample of articles, we used the Science Citation Index Expanded (SCI) from Thomson Reuters ISI Web of Science, as it is one of the most comprehensive databases of peer-reviewed journals in the sciences. Moreover, the SCI indexes more than 3,745 journals over 150 science subjects, adding around 60,000 new cited references per week.

A systematic research was conducted by searching for the keywords *Industry 4.0* and *cyber-physical systems* in Web of Science. The results were then refined by Web of Science Categories of Engineering Industrial, Engineering Manufacturing, Operations Research Management Science or Computer Science Interdisciplinary Applications resulting in 463 documents in English. These documents were used as input into *NAILS*, a bibliometric web-based software that uses a series of custom statistical and network analysis functions to provide a literature analysis using information from the chosen database (KNUTAS et al., 2015). The most relevant articles were selected according to the output of the analysis (shown in section 3) and were filtered by reviewing titles and abstracts, searching for the following keywords: *simulation-based optimization*, *dynamic manufacturing systems* and *adaptive scheduling.* Papers that were in non-relevant subject areas were excluded and further filtering the results by skimming through the remaining papers to find out the application area.

3. Literature analysis overview

All the papers reviewed were published in the last ten years. Figure 1 shows an increasing trend in publications.

Figure 1- Number of publications per year



The most influential authors are presented in fig. 2 in the form of a co-citation network, where co-citation is defined as the frequency in which two authors are cited together. The size of the author's node represents the amount of citations in total and the curved lines indicate authors that have been co-cited. The more times the authors have been co-cited, the stronger the connection.

The different clusters represent different research focuses. The red cluster, led by Jay Lee has special focus on Industry 4.0 and more practical applications. The blue cluster, led by László Monostori and Edward A. Lee, centers its research on the computational aspects of cyber physical systems, while the green cluster has its research focus on applications of cyber-physical system and collaborative manufacturing, targeting German industry specifically. Authors with less than 10 citations are not shown.

Figure 2 - Co-Citation Network

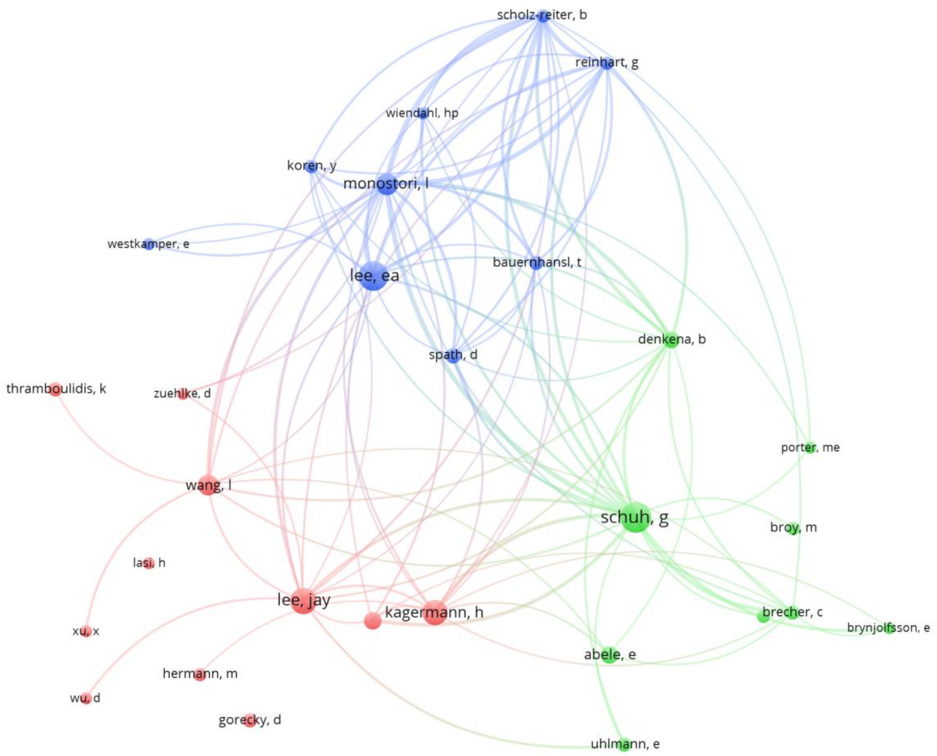


Figure 3 illustrates the systematic approach to the research. The bibliometric analysis was conducted after excluding the irrelevant subject areas.

Figure 3 - Systematic review methodology

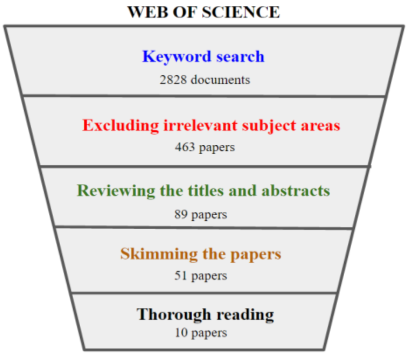


Table 1 shows the 10 articles that were deemed the most relevant to this research. These articles will be further discussed in the following sections.

Table 1. Top ten articles based on relevance and citations

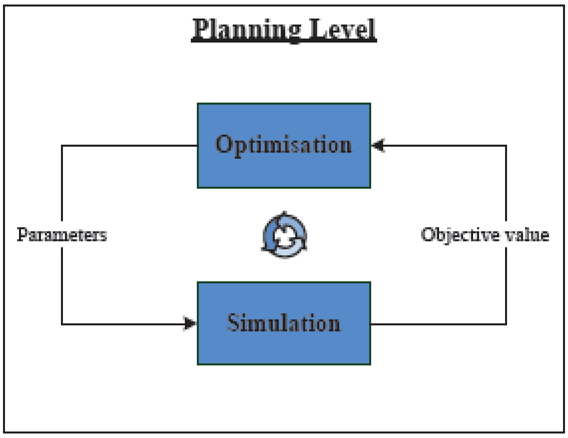
Year	Title	Author
2014	Cyber-physical production systems: Roots, expectations and R&D challenges	László Monostori
2014	Service innovation and smart analytics for Industry 4.0 and big data environment	Jay Lee, Hung-An Kao, Shanhu Yang
2014	Towards an understanding of cyber-physical systems as industrial software-product-service systems	M. Mikusz
2015	Current status and advancement of cyber-physical systems in manufacturing	Lihui Wang, Martin Törngren, Mauro Onori
2011	A simulation-based scheduling system for real-time optimization and decision making support	Marcus Frantzén, Amos H.C. Ng, Philip Moore
2012	Hybrid simulation based optimization approach for supply chain management	Amalia Nikolopoulou, Marianthi G. Ierapetritou
2014	Collaboration moves productivity to the next level	Günther Schuh, Till Potente, Rawina Varadani, Carlo Hausberg, Bastian Fränken
2016	Using autonomous intelligence to build a smart shop floor	Dunbing Tang, Kun Zheng, Haitao Zhang, Zelei Sang, Zequn Zhang, Chao Xu, Javier A. Espinosa Oviedo, Genoveva Vargas-Solar, José-Luis Zechinelli Martini
2013	RFID-enabled real time manufacturing execution system for mass-customization production	Ray Y. Zhong, Q.Y. Dai, T. Qu, G.J. Hu, George Q. Huang
2009	Simulation-based optimization vs. mathematical programming: A hybrid approach for optimizing scheduling problems	Andreas Klemmt, Sven Horn, Gerald Weigert, Klaus-Jürgen Wolter

4. Combining simulation and optimization in manufacturing systems

One of the most suitable ways to derive experience-based solutions to deal with real-world complex systems is through their modelling and simulation (LONGO, 2010). Simulation is a powerful tool for the analysis and evaluation of complex and stochastic systems such as manufacturing environments (LIN; CHEN, 2015), nonetheless it cannot provide an efficient optimization of these systems with respect to one or more performance indicators (lead times, production costs, etc.). On the other hand, optimization methods bring forth the challenge of solving the problem in a viable time. Therefore, simulation and optimization when approached individually are limited and often demand high effort when dealing with real problems. Long computational times and simulation constraints interfere when taking optimal decisions for complex and stochastic systems such as the scheduling of manufacturing systems.

A promising approach with the aim of combining the strengths of both is the simulation-based optimization (SBO) approach. In this setting, the simulation model is used as the objective function of the optimization and the optimization method determines the optimal configuration of parameters for the simulation (W. KRUG et al., 2002). Since the simulation model represents the real system in detail, it is not always necessary to express all relations of parameters analytically in the optimization model, which reduces the computational effort.

Figure 4 - Simulation-based optimisation approach



Nikopoulou and Ierapetritou (2012) proposed a hybrid simulation optimization approach that addresses a formulated supply chain management problem. The mathematical model was developed to minimize the sum of production cost, transportation cost, inventory holding and shortage costs. By coupling the MILP model to an agent based simulation model, the authors constructed a platform to investigate the quality of plans generated by the former. The two models worked in an iterative process, ensuring the best solution that can be implemented. The proposed approach was able to provide reasonable solutions in a short computational time.

Simplistically, a production scheduling task consists of defining jobs and sequences of these assigned jobs to machines. A simple schedule can be generated through standard dispatching rules, but that does not guarantee an optimal or even near-optimal schedule. When trying to model the problem mathematically, making assumptions such as that a schedule generated by dispatching rules is close to optimal can dramatically decrease the number of optimisation variables. Hence, a new schedule can be generated with less computational effort.

Ergo, the necessary computation time of the optimization decreases with the number of variables, which shows the great potential of simulation-based optimization. The idea of combining optimization and simulation is studied since the beginning of this millennium (FU, 2002) and has proven its strength in practical applications in the context of production and logistics systems.

Klemmt et al. (2009) formulated a mixed integer programming scheduling problem to analyse the present solvers capability and up to which complexity real scheduling problems are manageable. For further comparisons, the MIP model was coupled to a simulation model. It is the authors’ opinion that this interaction between the models is essential for solving real scheduling problems, especially if real-time conditions are needed.

It is noticeable, however, that the current approaches are limited to scenarios without dynamic influences. In reality, however, manufacturing environments are highly dynamic, so that an appropriate representation of the current system state requires an adaptation of the approach. In order to make the potential of SBO techniques available to the scheduling of dynamic production systems, there is a need to develop a data-driven adaptive model, which should harmonically develop with the new technologies being brought forth in the context of Industry 4.0. More specifically, cyber physical systems have the potential to integrate the simulation based optimization approach to more dynamic manufacturing systems by integrating processes, machines and products and sharing real-time information. With the required technology, the simulation model would be allowed to change during the optimization, so that schedules can be as dynamic as the system itself.

5. Adaptive scheduling

Scheduling can be defined as the assignment of a number of jobs, which have to be performed within a certain period of time, to the available resources (machines, tools and workers) of a production system (GE et al., 2014; JUNGWATTANAKIT et al., 2009). Optimizing production scheduling is essential for a high productive factory. Although there are varied methods to approach a scheduling problem, they are traditionally divided into three categories: analytic, heuristics and simulation (LEE, 2008). In regards to analytic methods, being that most scheduling problems, especially those emerging from real-world scenarios, are large-scale, complex, non-linear and highly uncertain, they therefore belong to the class of NP-hard optimisation problems. As a consequence of the complexity, optimal solutions often cannot be computed or only in extremely long computation times when modelled analytically. The analytical approach becomes applicable to reduced problems because of the inherent nature of scheduling problems (ODUGUWA et al. 2005).

Notwithstanding, Ku and Beck (2016) demonstrated the evolution of Mixed Integer Programming (MIP) by comparing different solvers. The authors showed that with modern solvers and computers moderate sized linear programming problems can be solved very quickly. However, high complexity scheduling problems, such as the job shop scheduling problem, still can't be solved analytically in an acceptable time and therefore its use by the industry is very limited.

This is the reason for the extensive use of heuristic methods in this context, which cannot guarantee optimal solutions but are often able to generate near-optimal solutions in relatively short computation time. One of the simplest and extensively utilized in industry heuristic scheduling methods is the use of dispatching rules, which means that each job in the queue of a machine is related with a priority value according to some predefined criteria. However, this approach has applicability limitations on dynamic systems, where there is a need for tight control and knowledge-based real-time decision making.

Manufacturing systems feature uncertain and stochastic events and its dynamic behaviour fosters frequent changes to the system setup, such as newly arriving job, rush orders or machine breakdowns. Due to the high degree of interdependencies between processes within production systems, disturbances can accumulate, so that even small changes of system parameters can have a big impact on the performance of the system. In literature, this is addressed by dynamic scheduling approaches, which can be divided into proactive and reactive approaches or a combination of both.

Proactive scheduling is often used when the uncertainty can be quantified in some way, so that stochastic events can already be taken into account by the schedule. Reactive scheduling approaches intend to react on the actual occurrence of disturbances. Proactive and reactive scheduling can also be combined to hybrid strategies, which consist of two phases: first, a robust schedule is computed. Then, during the execution of the schedule, it is observed if disturbances that exceed the tolerance of the schedule occur, thus making rescheduling necessary or a rescheduling is triggered periodically or a combination of both.

Zhong et al. (2013) proposed a manufacturing execution system assisted by RFID sensors for mass customization production in order to facilitate decision-making and making planning and sequencing more practical and precise. The proposed approach monitors disturbances along the production line in real-time and eliminates the need to manually collect data. The goal is to facilitate planning and control decisions by integrating the collected data into the operational logistics. Future research guidelines include the development of a mathematical model capable of using this data to plan the production.

Frantzén et al. (2011) presented an industrial application of simulation-based optimization (SBO) in the scheduling and real-time rescheduling of a complex machining line in an automotive manufacturer in Sweden. The authors described such a real-time scheduling system, which is in essence a SBO system integrated with the shop floor database system. The scheduling system uses real-time data from the production line and sends back expert suggestions directly to the operators. The results showed that such a novel scheduling system can help both in improving the line throughput efficiently and simultaneously supporting real-time decision making.

Rescheduling also yields the risk of poor performance, seeing that critical disruptions could occur while calculating a new schedule. However, with the current optimization approaches, analytical solution's computation times are likely to be prohibitive. Therefore, the need for information system technologies development is highlighted, considering that a real-time data sharing system could enable more flexibility in production control.

6. Cyber-physical systems

Cyber-physical systems (CPS) are systems comprised of collaborating computational entities integrated to information systems and intensively connected to the physical world and its processes. CPS research and applications have been leading the development of new technology in areas such as transportation, smart homes, robotic surgery, etc. (WANG et al. 2015). Due to the great potential for improved efficiency, CPS applications in manufacturing have the potential to lead a 4th Industrial Revolution, frequently noted as Industry 4.0 (FRAZZON et al., 2013; LEE et al. 2015).

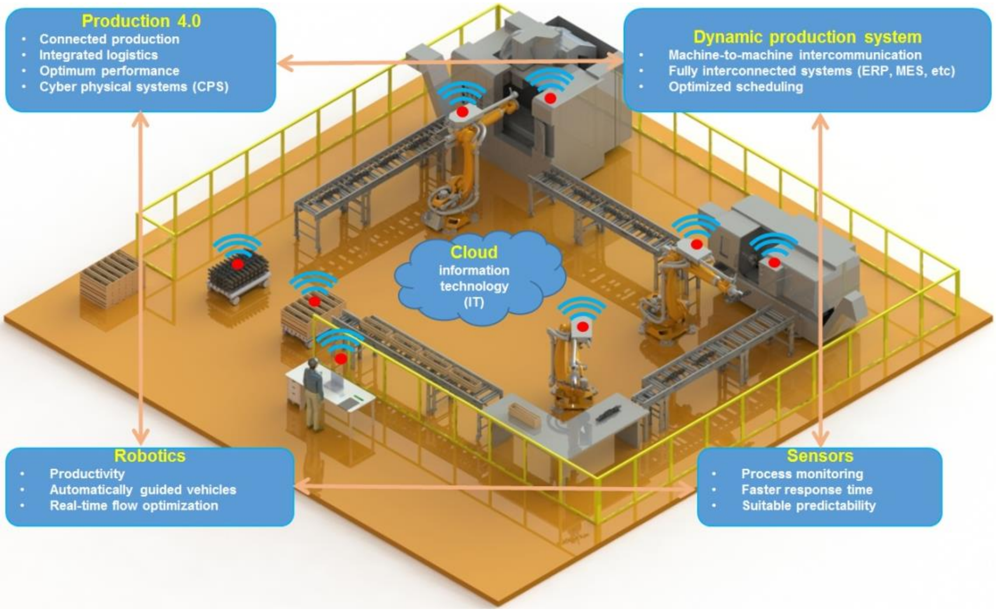
In modern manufacturing systems, machines interact with each other, operators, information systems and even products, exchanging information such as current status of production and problems that may demand maintenance. A cyber physical system within the industry is a network created by the integration of the physical aspect of a factory, such as machines or employees, with the cyber elements. Monostori (2014) describes the parallel development of computer science, communication technologies and manufacturing systems, identifying the convergences between these topics. The author cites many relations between the advancements in computer science and smart manufacturing, adding that the complex challenges of the industry leveraged interdisciplinary research. Cyber physical systems will enable real-time communication between humans, machines and products and are seen to be the tangible opportunity for a fourth industrial revolution.

Mikusz (2014) details the possibilities of applications of a product-service oriented cyber-physical system, citing that that CPS in the manufacturing environment comprises smart machines, storage systems and production processes capable of exchanging information. This facilitates any needed improvement to industrial processes along the manufacturing value chain. Production is also able to respond flexibly to disruptions and failures, with the possibility of mining data in real-time and having a communication system that enables the spread of this information to key components of the shop floor, integration of analytical and simulation-based approaches can be applied to dynamic manufacturing systems. The interaction between humans, machines and products is key for the development of smart manufacturing, where decision-making does not depend only on people but more on machines determining what it should do based on the current status of production. Wang et al. (2015) identify that in order to exploit cyber-physical systems full potential there is still a need for transition technologies, which would enable the introduction of ideas into the shop floor.

This new industrial phase is characterized by the use of sensors and networked machines and has led to a growth in the quantity of data being collected along the production processes through the communication of the many different parts of a manufacturing system. In this environment with a high volume of data, more accessible technologies CPS could be further developed order to achieve the goal of intelligent and self-learning manufacturing. Lee et al. (2015) identify the shop floor in an industry 4.0 as a collaborative community of machines, people and products. The authors describe the growing use of cyber-physical system as an inevitable trend. In this environment, the great quantity of data generated in the shop floor has the potential to revolutionize how production management works. The authors identify the processing of big data into useful information as the key of sustainable innovation within an industry 4.0 factory.

On the shop floor, the introduction of a cyber-physical system could facilitate architectures such as the one presented by Tang et al. (2016). Figure 5 illustrates the concept of a smart factory and highlights the need for interdisciplinary research.

Figure 5 - Shop floor integration architecture



Furthermore, the integration of cyber physical systems into more industrial aspects, such as logistics and services can transform today's factories into an Industry 4.0 factory, with big economic potential (LEE; KAO; YANG, 2014).

7. Conclusions

This study was conducted with the aim of reporting the state of the art in simulation-based optimisation for adaptive scheduling in dynamic environments within the context of cyber-physical systems. By systematically classifying the published literature, it is possible to outline research gaps and set directions for future research.

The performance of job shop manufacturing systems heavily relies on the influence of scheduling and control of production processes. In most cases, an optimisation is only done on a strategic level, while the shop floor control is performed on simple, static dispatching rules. On one hand, this enables the generation of schedules within short computational times. However, this approach does not guarantee optimal schedules and usually does not take into account the current state of the system.

The simulation-based optimisation approach has been successful in solving varied problems in industry. However, it shows limitations under dynamic environments. A growing need of new technology for real-time data sharing and automated decision making processes is identifiable as a barrier that restricts the SBO approach on dynamic manufacturing systems. The recent development of cyber-physical systems and industry 4.0 concepts and technologies identify a trend for future manufacturing systems. Scientific and praxis-oriented research potential is established on the integration of the dynamics of job shops and the concept of cyber physical systems, in such a way that scheduling decisions and the configuration of the shop floor control could be optimised with respect to the current state of the system. This integration should be based on the development of an iterative hybrid approach which allows changes in the objective function during the optimisation.

REFERENCES

FRANTZÉN, M.; NG, A. H. C.; MOORE, P. **A simulation-based scheduling system for real-time optimization and decision making support**, 2011.

FRAZZON, E. M. et al. Towards socio-cyber-physical systems in production networks. **Procedia CIRP**, v. 7, p. 49–54, 2013.

FU, M. C. Optimization for simulation: Theory vs. practice. **INFORMS Journal on Computing**, v. 14, n. 3, p. 192–215, 2002.

GE, J. H. et al. Research on Optimization Method of Real-time Available Resources for Dynamic Scheduling.

International Journal of Database Theory and Application, v. 7, n. 2, p. 91–98, 2014.

KAGERMANN, H.; WAHLSTER, W.; HELBIG, J. Recommendations for implementing the strategic initiative INDUSTRIE 4.0. **Final report of the Industrie 4.0 WG**, n. April, p. 82, 2013.

JUNGWATTANAKIT, J. et al. Algorithms for flexible flow shop problems with unrelated parallel machines, setup times, and dual criteria. **Computers and Operations Research**, v. 36, n. 2, p. 358–378, 2009.

KLEMMT, A. et al. Simulation-based optimization vs. mathematical programming: A hybrid approach for optimizing scheduling problems. **Robotics and Computer-Integrated Manufacturing**, v. 25, n. 6, p. 917–925, 2009.

KNUTAS, A. et al. Cloud-based bibliometric analysis service for systematic mapping studies. **ACM International Conference Proceeding Series**, v. 1008, n. 212, p. 184–191, 2015.

KU, W.-Y.; BECK, J. C. Mixed Integer Programming models for job shop scheduling: A computational analysis. **Computers & Operations Research**, v. 73, p. 165–173, 2016.

LEE, J.; BAGHERI, B.; KAO, H. A. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. **Manufacturing Letters**, v. 3, p. 18–23, 2015.

LEE, J.; KAO, H. A.; YANG, S. **Service innovation and smart analytics for Industry 4.0 and big data environment**. Procedia CIRP. **Anais**...2014

LEE, K. K. Fuzzy rule generation for adaptive scheduling in a dynamic manufacturing environment. **Applied Soft Computing**, v. 8, n. 4, p. 1295–1304, 2008.

LIN, J. T.; CHEN, C.-M. Simulation optimization approach for hybrid flow shop scheduling problem in semiconductor back-end manufacturing. **Simulation Modelling Practice and Theory**, v. 51, p. 100–114, 2015.

LONGO, F. Emergency Simulation: State of the Art and Future Research Guidelines. **SCS M&S Magazine**, v. 2, p. 1–8, 2010.

MIKUSZ, M. Towards an understanding of cyber-physical systems as industrial software-product-service systems. **Procedia CIRP**, v. 16, p. 385–389, 2014.

MONOSTORI, L. Cyber-physical production systems: Roots, expectations and R&D challenges. **Procedia CIRP**, v. 17, p. 9–13, 2014.

MULA, J. et al. Mathematical programming models for supply chain production and transport planning. **European Journal of Operational Research**, v. 204, n. 3, p. 377–390, 2010.

NIKOLOPOULOU, A.; IERAPETRITOU, M. G. Hybrid simulation based optimization approach for supply chain management. **Computers and Chemical Engineering**, v. 47, p. 183–193, 2012.

ODUGUWA, V.; TIWARI, A.; ROY, R. Evolutionary computing in manufacturing industry: an overview of recent applications. **Applied Soft Computing**, v. 5, n. 3, p. 281–299, 2005.

OKUBO, Y. Bibliometric Indicators and Analysis of Research Systems Methods and Examples. **OECD Science, Technology and Industry Working Papers 1997/01**, 1997.

TANG, D. et al. Using Autonomous Intelligence to Build a Smart Shop Floor. **Procedia CIRP**, v. 56, p. 354–359, 2016.

URIONA-MALDONADO, M.; DOS SANTOS, R. N. M.; VARVAKIS, G. State of the art on the Systems of Innovation research: A bibliometrics study up to 2009. **Scientometrics**, v. 91, n. 3, p. 977–996, 2012.

W. KRUG, TH. WIEDEMANN, J. LIEBELT, B. B. et al. Simulation and Optimization in Manufacturing , Organization and Logistics. **Simulation in Industry, 14th European Simulation Symposium**, p. 423–429, 2002.

WANG, L.; TÖRNGREN, M.; ONORI, M. Current Status and Advancement of Cyber - Physical Systems in Manufacturing. v. XXX, p. 1–18, 2015.

ZHONG, R. Y. et al. RFID-enabled real-time manufacturing execution system for mass-customization production. **Robotics and Computer-Integrated Manufacturing**, v. 29, n. 2, p. 283–292, 2013.